

Marketing Magic or Just Hype? The AI Factor in Indonesia's MSME Growth

**Johni Eka Putra¹, Lili Adi Wibowo², Siska Armawati Sufa³, Nindi Aristi⁴,
Irzameingindra Putri Radjamin⁵**

Pendidikan Indonesia University, Indonesia^{1,2}
Dr. Soetomo University Surabaya, Indonesia³
Padjadjaran University Bandung, Indonesia⁴

Faculty of Business and Economics, Surabaya University, Indonesia⁵

johniekaputra@upi.edu¹, siska.armawati@unitomo.ac.id², liliadiwibowo.edu@upi.edu³,
nindi.aristi@unpad.ac.id⁴, irza@staff.ubaya.ac.id⁵

Article Info

Received: 2025-01-20

Revised: 2025-03-28

Accepted: 2025-05-28

Keywords:

*Competitive Advantage,
Innovation Diffusion,
MSMEs, Technology
Adoption*

Abstract

This research investigates the strategic influence of artificial intelligence (AI) adoption on the competitiveness of Micro, Small, and Medium Enterprises (MSMEs) in Indonesia, emphasizing the mediating role of innovation diffusion. By synthesizing the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Resource-Based View (RBV), the study analyzes how perceived usefulness and ease of use contribute to the attainment of sustained competitive advantage. Employing a quantitative methodology, the analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data collected from 160 MSMEs. The measurement model demonstrated strong reliability and validity. The findings reveal that technology adoption exerts a significant effect on both innovation and competitiveness, with innovation serving as a partial mediator. The R^2 and Q^2 values reflect moderate explanatory and predictive capacity. This study provides both theoretical contributions and practical recommendations for fostering digital transformation in the MSME sector through AI-driven innovation.

A. INTRODUCTION

The global digital transformation has redefined how businesses operate, particularly in emerging economies. In Indonesia, Micro, Small, and Medium Enterprises (MSMEs) form the backbone of the national economy, contributing over 60% to the country's GDP and employing more than 97% of the workforce (Kadin Indonesia, 2023). However, MSMEs continue to face challenges in maintaining competitiveness, especially in light of rapidly evolving technological landscapes. As digitalization becomes essential rather than optional, MSMEs are increasingly pressured to integrate digital tools to sustain their market relevance and expand operational efficiency.

Generally, marketing is carried out in common ways, such as distributing flyers, promoting through social media, or using endorsements from influencers (Abdillah et al., 2024). In recent years, artificial intelligence (AI) has emerged as a hot topic in management and marketing sciences (Krisprimandoyo, 2023). Recent advancements in Artificial Intelligence (AI) have introduced transformative potential in digital marketing and operational decision-making for MSMEs. Tools such as chatbots, AI-driven analytics, and automated content generation systems offer significant improvements in customer engagement and strategic planning (Khaq, 2024; Santosa, 2024). AI adoption is associated with increased sales and enhanced customer satisfaction, with approximately 70% of MSMEs in Indonesia reporting performance improvements post-adoption (Khaq, 2024). Despite these benefits, the pace and effectiveness of AI adoption vary widely, largely due to gaps in AI literacy and uneven access to technological infrastructure across different regions.

The adoption of technology among MSMEs in Indonesia is no longer a novel trend but a necessary response to globalization and market dynamism. However, a persistent problem remains: how can MSMEs move beyond basic digital usage and leverage technology strategically to create lasting competitive advantages? Existing literature has focused on individual aspects such as digital literacy, marketing tools, or operational performance, but comprehensive models integrating technology adoption, innovation diffusion, and strategic outcomes remain limited, particularly in emerging economies.

To address this, the current study proposes an integrated approach that

combines three influential theoretical lenses: the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), and the Resource-Based View (RBV). This framework investigates how perceived benefits and usability drive adoption, how innovation characteristics influence diffusion, and how internal resources shaped by innovation generate sustained advantages. This holistic lens offers a general solution to guide MSMEs in optimizing technology strategically.

The Technology Acceptance Model (TAM), developed by Davis (1989), has been extensively used to explain users' behavioral intentions toward technology. It posits that two primary perceptions usefulness and ease of use directly impact adoption behavior. For MSMEs, these perceptions govern decisions to integrate AI tools, especially under resource constraints and skill gaps. Empirical studies have validated TAM's applicability in small-business contexts, making it a suitable lens for examining how Indonesian MSMEs adopt AI for business transformation (Venkatesh & Davis, 2000).

Building on adoption, the Diffusion of Innovations (DOI) theory proposed by Rogers (1983) introduces a process-oriented perspective on how innovations spread. Key attributes such as relative advantage, compatibility, complexity, trialability, and observability influence how innovations like AI are absorbed into MSME structures. Research by Modgil et al. (2021) and Mukherjee (2023) show how these attributes impact the pace and breadth of digital technology adoption, particularly in marketing and supply chain systems. This perspective is instrumental in understanding the internal mechanisms of how technology translates from novelty to normalized practice.

The Resource-Based View (RBV), as developed by Barney (2015), emphasizes internal firm resources as the primary drivers of sustained competitive advantage. When MSMEs deploy AI as a resource that is valuable, rare, inimitable, and non-substitutable (VRIN), it can transform operational efficiencies into strategic strengths. Seriki (2020) reinforces that digital capabilities, when appropriately diffused and embedded in the organization, elevate MSMEs' capacity to compete beyond pricing and proximity. Thus, combining TAM, DOI, and RBV provides a theoretically robust framework to guide this investigation.

Numerous studies have examined the adoption of digital technologies

among MSMEs, highlighting both motivators and barriers. For example, Islami et al. (2020) demonstrated that AI tools enhance sales performance, while Pranata (2024) linked AI integration with improved SEO and customer targeting. However, these studies often isolate technology adoption from its broader strategic outcomes, failing to connect these interventions to competitive advantage frameworks such as RBV.

Similarly, while diffusion research has underscored the role of innovation characteristics in adoption speed and reach (Tresnasari & Zulganef, 2023), the literature lacks empirical models that position innovation diffusion as a mediator between technology adoption and competitiveness. The strategic interplay among TAM, DOI, and RBV has not been empirically tested in Indonesia's MSME context, where infrastructural disparities and AI literacy gaps are pronounced.

This research fills the gap by testing a comprehensive model that links AI-driven technology adoption to competitive advantage through innovation diffusion. It evaluates not only the direct impacts but also the mediating pathways that determine strategic success. By focusing on Indonesian MSMEs, the study responds to calls for more localized and context-sensitive frameworks that account for emerging market complexities (Cueto et al., 2022; Nurlina et al., 2023).

The primary objective of this study is to examine how AI-based technology adoption impacts the competitive advantage of Indonesian MSMEs, with innovation diffusion serving as a mediating mechanism. This investigation is grounded in the integration of TAM, DOI, and RBV frameworks to explore both behavioral and strategic dimensions of technology utilization. The study tests key relationships among perceived usefulness, innovation attributes, and competitive resources within a single empirical model using PLS-SEM.

This research contributes novelty by empirically linking three theoretical frameworks in the specific context of Indonesia's MSME digital transformation. While previous studies have addressed individual constructs, none have synthesized these models to explore how MSMEs move from technology adoption to strategic competitiveness via innovation diffusion. Geographically, the study focuses on MSMEs across Indonesia's provinces.

Contextually, it emphasizes AI integration in marketing and operations. The findings are expected to offer both academic insights and actionable strategies for policy-makers and business leaders navigating the digital economy.

Technology adoption in Micro, Small, and Medium Enterprises (MSMEs) has emerged as a crucial determinant of performance in digital economies. The Technology Acceptance Model (TAM), introduced by Davis (1989), posits that two core beliefs Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) influence a user's intention to adopt and utilize technology. PU reflects the degree to which a user believes that using a system would enhance their job performance, while PEOU refers to the belief that using a system will be free of effort. Numerous empirical studies have confirmed the relevance of TAM across diverse technological contexts, including e-commerce, digital marketing, and AI integration (Islami et al., 2020; Venkatesh & Davis, 2000).

In the context of Indonesian MSMEs, where digital maturity varies widely, TAM provides a foundational lens to evaluate digital readiness and the likelihood of successful technology adoption. Studies have shown that higher levels of PU and PEOU significantly improve digital tool utilization, which in turn enhances operational efficiency and market responsiveness (Wang et al., 2022). The strategic application of AI-driven tools such as chatbots and data analytics can simplify processes and improve marketing outcomes when users perceive them as easy to use and beneficial (Modgil et al., 2021). Thus, understanding technology adoption through TAM can predict MSME engagement with digital transformation. Thus, the following hypotheses is formulated:

H1: Technology Adoption (TAM) positively influences Innovation Diffusion (DOI).

Innovation diffusion refers to the process through which new technologies or ideas spread within and across organizations. Rooted in Rogers & Everett (1983) Diffusion of Innovations Theory, five core attributes determine the adoption and spread of innovations: Relative Advantage (RA), Compatibility (C), Complexity (CX), Trialability (TR), and Observability (OB). RA reflects the degree to which an innovation is perceived as superior to existing solutions, while compatibility refers to its alignment with existing values and practices. Complexity denotes perceived difficulty, TR allows for

experimentation, and OB reflects the visibility of benefits.

For MSMEs, particularly in developing economies like Indonesia, the diffusion process is critical in bridging the gap between technology acquisition and performance impact. Empirical evidence indicates that firms with high innovation diffusion capacity benefit from faster adoption cycles and better alignment of technology with strategic goals (Cueto et al., 2022). The adoption of AI tools for marketing, for instance, requires not only technical capability but also an organizational environment conducive to experimentation and adaptation. Innovation diffusion thus acts as a transformative mechanism, enabling firms to translate technology adoption into competitive advantage. Accordingly, the following hypotheses are stated:

H2: Innovation Diffusion (DOI) positively influences Competitive Advantage (RBV).

H4: Innovation Diffusion (DOI) mediates the relationship between Technology Adoption (TAM) and Competitive Advantage (RBV).

The Resource-Based View (RBV) framework emphasizes the strategic value of internal firm resources in sustaining competitive advantage (Barney, 2015). According to RBV, resources must be Valuable (V), Rare (R), Inimitable (I), and Non-substitutable (N) collectively referred to as VRIN attributes to yield long-term benefits. In the digital age, technology capabilities particularly those enhanced by AI can serve as strategic resources if they meet the VRIN criteria (Seriki, 2020).

MSMEs that successfully integrate and diffuse digital innovations can develop unique competencies that enhance market responsiveness, customer engagement, and operational agility. The integration of AI in digital marketing, for example, enables personalized content, predictive analytics, and customer segmentation all of which contribute to competitive positioning (Mukherjee, 2023; Santosa, 2024). However, the mere presence of technology is insufficient; its strategic utilization and organizational embedding are essential for value creation. Thus, competitive advantage arises not solely from technology acquisition but from the ability to transform it into a unique, inimitable capability. Thus, the subsequent hypothesis is expressed as follows:

H3: Technology Adoption (TAM) positively influences Competitive Advantage (RBV).

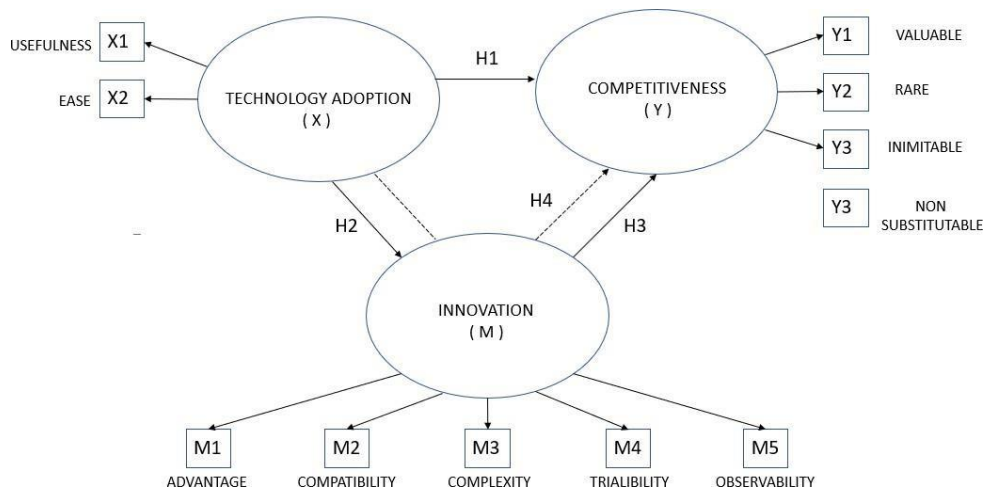


Figure 1. Conceptual Framework

B. RESEARCH METHODS

This study employs a quantitative, cross-sectional research design to explore the relationship between AI literacy, innovation diffusion, and MSME competitiveness. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as the analytical method, as it is well-suited for examining complex relationships among latent variables (J. Hair et al., 2019). To ensure a diverse representation of MSMEs across different industries retail, services, and manufacturing as well as varying levels of AI adoption (low, moderate, and high), a stratified random sampling technique was applied. A structured survey was distributed to 180 MSME owners and managers, resulting in 160 valid responses. The responses were measured using a 5-point Likert scale to assess AI literacy, digital marketing effectiveness, and perceived competitiveness. The chosen sample size of 180 MSMEs aligns with prior studies utilizing PLS-SEM (J. Hair et al., 2019), ensuring sufficient statistical power for analyzing latent variables while balancing practical constraints. In line with, A 5-point Likert scale was chosen over a 7-point scale due to its simplicity and effectiveness in ensuring reliable responses from MSME owners with varying levels of AI literacy. Participants provided informed consent, and their data anonymity was maintained in accordance with GDPR and

Indonesian privacy laws.

C. RESULTS AND DISCUSSION

Relevance of Curriculum

The measurement model was evaluated using indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), all of which demonstrate strong evidence of reliability and validity.

Table 1. Table of Loading, Cronbach'alpha, composite reliability (CR), and AVE

Variables/Indicators	Loading	Alpha	CR	AVE
Competitiveness		0.877	0.915	0.73
Digital tools improve business performance	0.913			
Digital tools are easy to use	0.911			
Innovation		0.833	0.883	0.6
Digital innovation offers clear advantages	0.746			
Digital tools align with business practices	0.751			
Digital innovation is difficult to understand/use	0.881			
Digital tools can be tested before full use	0.818			
The benefits of digital tools are visible to others	0.676			
Technology Adoption		0.797	0.908	0.83
Digital resources add value to the business	0.889			
Digital strategies are rare among competitors	0.896			
My digital advantages are hard to imitate	0.752			
No substitutes can replace my digital capabilities	0.872			

All indicator loadings exceeded the recommended threshold of 0.70, indicating that each item strongly reflects its underlying construct (J. F. Hair et al., 2021). Cronbach's alpha values for Competitiveness (0.877), Innovation (0.833), and Technology Adoption (0.797) all surpassed the acceptable

minimum of 0.70, confirming adequate internal consistency. Similarly, composite reliability values (ρ_C) for all constructs were well above the recommended threshold of 0.70—Competitiveness (0.915), Innovation (0.883), and Technology Adoption (0.908)—signifying robust construct reliability (J. F. Hair et al., 2021). Moreover, the AVE values for Competitiveness (0.73), Innovation (0.60), and Technology Adoption (0.83) all exceeded the 0.50 benchmark, providing evidence of convergent validity as each construct explained more than 50% of the variance in its indicators (Fornell & Larcker, 1981). Collectively, these results confirm that the measurement model possesses satisfactory psychometric properties and is suitable for structural equation modeling.

The cross-loading analysis is a methodological approach that aims to confirm discriminant validity. This analysis demonstrates that each indicator exhibits a higher loading on its intended construct than on other constructs. This contributes to the distinctiveness of each construct and reinforces the overall validity of the measurement model.

Table 2. Cross loading

	Competitiveness	Innovation	Technology Adoption
X1	0.453	0.559	0.913
X2	0.464	0.538	0.911
M1	0.397	0.746	0.403
M2	0.444	0.751	0.434
M3	0.494	0.881	0.496
M4	0.415	0.818	0.468
M5	0.371	0.676	0.525
Y1	0.889	0.487	0.428
Y2	0.896	0.467	0.447
Y3	0.752	0.33	0.24
Y4	0.872	0.544	0.533

As demonstrated in the accompanying table, the entirety of the indicators meet this criterion. For instance, indicators X1 and X2 load most strongly on Technology Adoption (0.913 and 0.911, respectively), compared to their lower loadings on Innovation (0.559, 0.538) and Competitiveness (0.453, 0.464). In a similar vein, indicators M1 through M5 demonstrate their highest loadings on the Innovation construct (ranging from 0.676 to 0.881), which significantly

surpass their cross-loadings on Competitiveness and Technology Adoption. Finally, indicators Y1 to Y4 load strongest on Competitiveness (with values between 0.752 and 0.896), clearly higher than their respective loadings on the other two constructs. These findings confirm that each indicator has the highest association with its own construct, thereby satisfying the discriminant validity requirement using the cross-loading criterion. This finding serves to reinforce the distinctiveness of the construct that was established earlier through the application of the Fornell-Larcker analysis. Furthermore, it serves to affirm that the measurement model is both theoretically and empirically robust (J. F. Hair et al., 2021).

In addition to the evidence provided by the cross-loading criterion, the Fornell-Larcker approach offers a complementary method to assess discriminant validity at the construct level. By comparing the square root of each construct's AVE with its correlations to other constructs, this technique ensures that the latent variables are empirically distinct at the indicator level and also remain conceptually unique in their overall relationships with other constructs.

The Fornell-Larcker criterion constitutes a widely utilized method for assessing discriminant validity in structural equation modeling. The square root of the Average Variance Extracted (AVE) for each latent construct is compared with the correlations between that construct and others in the model. According to Fornell and Larcker (1981), discriminant validity is established when the square root of a construct's AVE (displayed on the diagonal of the matrix) is greater than its correlations with any other construct (off-diagonal values).

Table 3. Fornell-Larcker Criterion

	Competitiveness	Innovation	Technology Adoption
Competitiveness	0.854		
Innovation	0.548	0.777	
Technology Adoption	0.503	0.602	0.912

As illustrated in the presented table, the square roots of AVE for Competitiveness (0.854), Innovation (0.777), and Technology Adoption (0.912) are all higher than their respective inter-construct correlations—

Competitiveness-Innovation (0.548), Competitiveness-Technology Adoption (0.503), and Innovation-Technology Adoption (0.602). This finding aligns with the Fornell-Larcker criterion, thereby substantiating the construct's discriminant validity and its greater shared variance with its own indicators as opposed to other constructs. Consequently, the constructs in this model are empirically distinct, thereby supporting the robustness of the measurement model and ensuring the validity of subsequent structural path analysis (Fornell & Larcker, 1981; J. F. Hair et al., 2021).

Table 4. Heterotrait-Monotrait Ratio (HTMT)

	Competitiveness	Innovation	Technology Adoption
Competitiveness			
Innovation	0.625		
Technology Adoption	0.576	0.737	

The Heterotrait-Monotrait Ratio (HTMT) is a contemporary and more rigorous method for assessing discriminant validity in structural equation modeling. Its use is particularly recommended in conjunction with variance-based approaches, such as PLS-SEM. According to Henseler et al. (2015), discriminant validity is established when the HTMT value between two constructs is below 0.90 in general research contexts and more conservatively below 0.85 in more strict conditions. The values in the presented HTMT table 0.625 between Competitiveness and Innovation, 0.576 between Competitiveness and Technology Adoption, and 0.737 between Innovation and Technology Adoption are all well below both the 0.90 and 0.85 thresholds. These results confirm that the constructs are empirically distinct from one another, thereby reinforcing discriminant validity and ensuring that each construct captures a unique aspect of the theoretical model. Therefore, the HTMT assessment corroborates the structural model's overall robustness and measurement integrity.

In summary, the measurement model demonstrates strong reliability and validity. All constructs demonstrate high internal consistency and convergent validity, while discriminant validity is confirmed through cross-loadings, the Fornell-Larcker criterion, and HTMT ratios. These results suggest that the

model is both robust and appropriate for further structural analysis.

Structural Model

The initial step is the evaluation of the relationships between the latent constructs based on the proposed hypotheses. The present phase is focused on the assessment of the model's explanatory power, predictive relevance, and the significance of path coefficients. The Variance Inflation Factor (VIF) is used in PLS-SEM to detect multicollinearity among indicators, ensuring that predictors do not excessively overlap in the variance they explain. According to Hair et al. (2021), VIF values below 5.0 indicate acceptable collinearity, while values under 3.3 are preferred for minimal concern. In the table, all VIF values fall within the acceptable range, with the highest being M3 (3.003), Y2 (2.930), and Y1 (2.811), none of which exceed the threshold.

Table 5. Collinearity Statistics

	VIF
Innovation -> Competitiveness	1.567
Technology Adoption -> Competitiveness	1.567
Technology Adoption -> Innovation	1

The collinearity statistics, as indicated by VIF values ranging from 1.000 to 1.567, demonstrate that all predictor constructs in the model exhibit low multicollinearity, well below the recommended thresholds of 3.3 or 5.0 (Hair et al., 2021). This finding serves to substantiate the hypothesis that the structural model is free from collinearity issues, thereby ensuring the reliability and interpretability of the path coefficient estimates.

Table 6. R Square

	R-square	R-square adjusted
Competitiveness	0.348	0.342
Innovation	0.362	0.359

The R-squared (R^2) values indicate that the structural model demonstrates

moderate explanatory power, with 34.8% of the variance in competitiveness and 36.2% in innovation explained by their respective predictors. According to Hair et al. (2021), these values fall within the acceptable range for moderate predictive strength. The adjusted R^2 values, which remain close to the unadjusted ones, further confirm the model's stability. The findings indicate that the model demonstrates adequate predictive accuracy and that the hypothesized structural relationships are empirically substantiated and significant.

Table 7. R Square

	SSO	SSE	$Q^2 (=1 - SSE/SSO)$
Competitiveness	912	698.401	0.234
Innovation	1140	902.179	0.209
Technology Adoption	456	456	0

The Q^2 values indicate that the structural model possesses moderate predictive relevance for the endogenous constructs, with Competitiveness (0.234) and Innovation (0.209) both exceeding the recommended threshold of 0.15 (J. F. Hair et al., 2021). This finding suggests that the model can effectively predict these constructs. Conversely, the Q^2 value for Technology Adoption is 0, a finding that aligns with its role as an exogenous variable in the model, thereby precluding its prediction. In summary, the findings substantiate the model's satisfactory predictive capacity and reinforce its empirical soundness.

The following table presents the hypothesis testing results derived from the structural model in PLS-SEM, evaluating the significance of relationships among the latent variables. According to Hair et al. (2021), a T-statistic greater than 1.96 (at a 5% significance level) and a p-value less than 0.05 are indicative of a hypothesized path being statistically significant. In this table, all hypotheses (H1 to H4) meet these criteria, with p-values of 0 and T-statistics well above 1.96, indicating strong empirical support for all proposed relationships.

Table 8. Table of Hypothesis

	(O)	(M)	(STDEV)	T statistic	P values
H1: Technology Adoption influences Innovation Diffusion	0.6	0.6	0.053	11.26	0
H2: Innovation Diffusion influences Competitive Advantage	0.39	0.39	0.082	4.674	0
H3: Technology Adoption influences Competitive Advantage	0.5	0.51	0.064	7.821	0
H4: Innovation Diffusion mediates the relationship between Technology Adoption and Competitive Advantage	0.23	0.23	0.059	3.947	0

For H1, the path coefficient (O) between Technology Adoption and Innovation Diffusion is 0.6 with a T-statistic of 11.26, suggesting a strong and significant positive influence. H2 indicates that Innovation Diffusion exerts a substantial influence on Competitive Advantage, as evidenced by its coefficient of 0.39 and a T-statistic of 4.674. This finding further substantiates the significance of the observed effect. H3 indicates a direct impact of technology adoption on competitive advantage ($\beta = 0.5$), as evidenced by a substantial T-statistic of 7.821, thereby substantiating its significance. Finally, H4 examines the mediation effect of Innovation Diffusion in the relationship between Technology Adoption and Competitive Advantage, showing a statistically significant indirect effect with a coefficient of 0.23 and a T-statistic of 3.947.

These findings substantiate the notion that technology adoption exerts a direct influence on competitive advantage, in addition to an indirect impact via innovation diffusion, thereby validating a partial mediation model. The findings, when considered collectively, serve to validate the theoretical framework and suggest that innovation diffusion is a critical mechanism through which digital adoption translates into strategic advantage for MSMEs.

DISCUSSION

The findings of this study offer strong empirical evidence supporting the theoretical framework that integrates the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Resource-Based

View (RBV) in the context of Indonesian MSMEs. The structural model confirms that technology adoption exerts a substantial influence on both innovation diffusion and competitive advantage, with path coefficients of 0.60 and 0.50, respectively. These findings corroborate the Technology Acceptance Model (TAM) proposition that perceived usefulness and ease of use drive technology adoption (Davis et al., 1989), and extend it by linking technology acceptance to tangible business outcomes, such as enhanced competitiveness. Furthermore, the substantial impact of innovation diffusion on competitive advantage ($\beta = 0.39$), in conjunction with its mediating function in the relationship between technology adoption and competitiveness ($\beta = 0.23$), underscores the significance of DOI attributes such as trialability, observability, and relative advantage (Rogers & Everett, 1983). The findings indicate that innovation diffusion plays a pivotal role in the internalization and utilization of technological tools, particularly AI-based solutions, for the attainment of strategic advantages.

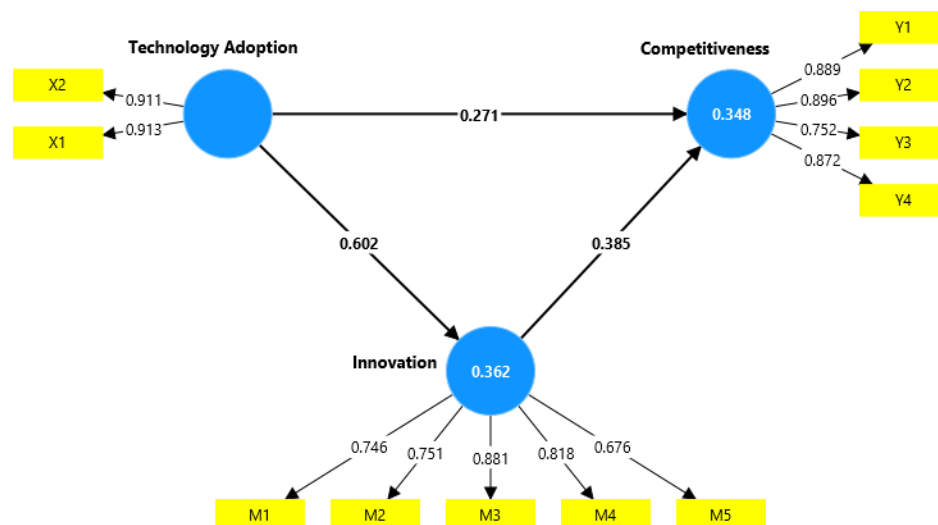


Figure 2. PLS-SEM Structural Model: The Influence of Technology Adoption on Competitiveness through Innovation

From a theoretical standpoint, the study contributes to the advancement of TAM by empirically validating its integration with DOI and RBV in a single structural model. While TAM focuses on the initial decision to adopt, DOI provides a deeper understanding of how innovations are disseminated within

organizations, and RBV explains how such processes contribute to sustained competitive advantage. The integration of these models in the study serves to bridge the gap between behavioral intent and strategic impact, thereby demonstrating that the adoption and diffusion of digital tools within firm routines is essential for yielding VRIN-based resources (Barney, 2015). The predictive relevance (Q^2) of 0.234 for competitiveness and 0.209 for innovation, along with the moderate R^2 values, reinforce the model's explanatory and predictive validity. The absence of multicollinearity, as indicated by all VIFs being less than 5, serves to further affirm the model's structural integrity, thereby enabling reliable interpretation of the inter-construct relationships.

Theoretically, this study contributes to the existing discourse on digital transformation in emerging markets by conceptualizing innovation diffusion as a strategic conduit between technology adoption and performance outcomes. In the context of AI integration, MSMEs must consider two factors. First, they must consider usability (TAM). Second, they must consider the organizational readiness to trial, observe, and scale digital innovations (DOI). The successful execution of this diffusion process enables firms to develop resources that are valuable, rare, difficult to imitate, and non-substitutable (RBV), thereby ensuring sustained competitive advantage. This framework is particularly pertinent for Indonesian MSMEs navigating the complexities of digital transformation amid infrastructure challenges and uneven digital literacy levels. Furthermore, it offers a robust theoretical framework for future research exploring the pathways through which emerging technologies translate into strategic capabilities.

The study underscores a number of pragmatic strategies for enhancing the adoption of AI and digital performance among MSMEs. It is imperative for business leaders to prioritize not only the implementation of AI technologies, such as chatbots and data analytics, but also the cultivation of a workplace culture that fosters innovation diffusion. The establishment of an environment conducive to the testing, observation, and integration of new technologies with existing operations has the potential to enhance their effectiveness and strategic value. Moreover, enhancing AI literacy is imperative. The provision of training that enhances comprehension and perceived utility of AI tools has been demonstrated to exert a substantial influence on adoption and sustained

utilization, particularly when supplemented by targeted government and institutional programs in under-resourced regions.

Furthermore, policymakers play a pivotal role in facilitating MSMEs' digital transformation by offering financial incentives, developing infrastructure, and establishing policy frameworks that reduce barriers to AI integration. This support has been demonstrated to enhance not only the competitiveness of individual firms but also the economic resilience of nations. It is incumbent upon technology developers to ensure that AI tools are designed with the unique constraints and needs of MSMEs in mind, offering user-friendly, customizable solutions that address specific industry challenges. Collective initiatives among businesses, governments, and developers can facilitate digital adoption, encourage innovation, and promote sustainable growth for MSMEs.

While the structural model demonstrated moderate explanatory power, evidenced by R^2 values of 0.348 for Competitiveness and 0.362 for Innovation, it indicates that a considerable portion of variance remains unaccounted for. This finding suggests the possibility of the presence of additional influential variables that have not been examined and which may play a significant role. The model's scope, while informative, omits contextual factors such as market dynamics, regulatory environments, and firm-specific traits like leadership style or digital maturity. These contextual factors could further enhance the model's predictive strength and theoretical robustness.

To address these gaps, future research should integrate external and organizational-level factors that potentially affect technology adoption and competitive advantage. The employment of longitudinal or experimental designs would facilitate more robust causal analysis and a more profound understanding of how these relationships evolve over time. Moreover, extending the scope of the study to encompass MSMEs from additional developing countries or diverse industrial sectors could enhance the generalizability of the TAM– DOI–RBV framework, thereby offering a more comprehensive perspective on digital transformation across a range of socio-economic and institutional contexts.

E. CONCLUSION

This study has empirically validated a comprehensive model that integrates the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Resource-Based View (RBV) to examine the role of technology adoption and innovation diffusion in enhancing the competitive advantage of Indonesian MSMEs. The findings indicate that technology adoption exerts a direct influence on competitive advantage and an indirect influence through innovation diffusion, thereby substantiating the existence of partial mediation. The structural model assessments indicate moderate explanatory power and predictive relevance, thereby supporting the robustness and validity of the proposed framework. The measurement model has been demonstrated to satisfy the criteria for reliability and validity, as evidenced by high factor loadings, strong composite reliability, and acceptable AVE values. Furthermore, discriminant validity was well established using the Fornell-Larcker criterion, cross-loading analysis, and HTMT ratios.

The study underscores the significance of two key factors. Firstly, it emphasizes the adoption of digital technologies, particularly those that are driven by artificial intelligence. Secondly, it underscores the necessity of ensuring the effective dissemination of these technologies within organizational practices. The dual pathway of adoption and diffusion enables MSMEs to transform technological investments into strategic resources that offer long-term competitive advantage. Consequently, the incorporation of artificial intelligence (AI) and digital advancements must be regarded not solely as operational enhancements but as strategic imperatives for the growth and sustainability of micro, small, and medium-sized enterprises (MSMEs) within Indonesia's evolving digital economy.

References

- Abdillah, A., Sufa, S. A., & Brumadyadisty, G. (2024). "HAPPY BARENG BIGGER BETTER " SCHOOL TO SCHOOL DI SURABAYA. 9(1), 266–284.
- Barney, J. (2015). Firm resources and sustained competitive advantage. *International Business Strategy: Theory and Practice*, 17(1), 283–301. <https://doi.org/10.1093/oso/9780199277681.003.0003>
- Cueto, L. J., Frisnedi, A. F. D., Collera, R. B., Batac, K. I. T., & Agaton, C. B. (2022). Digital Innovations in MSMEs During Economic Disruptions: Experiences and Challenges of Young Entrepreneurs. *Administrative Sciences*, 12(1), 8.

- <https://doi.org/10.3390/admsci12010008>
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, 35(8), 982–1003. <https://doi.org/10.1287/mnsc.35.8.982>
- European Economic Letters. (2024). “Unlocking Digital Potential: Navigating the Path to Digital Transformation for Indian MSMES.” <https://doi.org/10.52783/eel.v14i1.1314>
- Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Evaluation of Formative Measurement Models*. https://doi.org/10.1007/978-3-030-80519-7_5
- Hair, J., Marko Sarstedt, Hopkins, L., & Kuppelwieser, V. (2019). Partial least squares structural equation modeling (PLS-SEM) An emerging tool in business research. *European Business Review*, 26(2). <https://doi.org/10.1108/EBR-10-2013-0128>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Islami, N. N., Wahyuni, S., & Tiara, T. (2020). The Effect of Digital Marketing on Organizational Performance Through Intellectual Capital and Perceived Quality in Micro, Small and Medium Enterprises. *Jurnal Organisasi Dan Manajemen*, 16(1), 60–72. <https://doi.org/10.33830/jom.v16i1.718.2020>
- Kadin Indonesia. (2023). UMKM Indonesia - KADIN Indonesia. In *Kadin Indonesia* (p. 1). Indonesian Chamber of Commerce and Industry. <https://kadin.id/data-dan-statistik/umkm-indonesia/>
- Khaq, Z. D. (2024). AI-driven Strategies for Enhancing MSME Sales and Business Communication: A Case Study. *Jmi*, 3(2), 180–194. <https://doi.org/10.51903/jmi.v3i2.28>
- Krisprimandoyo, D. A. (2023). Optimizing Corporate Branding: The Role of Artificial Intelligence In Business Transformation of IQOS. *Jurnal Riset Multidisiplin dan Inovasi Teknologi*, 2(01), 283–306. <https://doi.org/10.59653/jimat.v2i01.482>
- Modgil, S., Singh, R., & Hannibal, C. (2021). Artificial Intelligence for Supply Chain Resilience: Learning From Covid-19. *The International Journal of Logistics Management*, 33(4), 1246–1268. <https://doi.org/10.1108/ijlm-02-2021-0094>
- Mukherjee, S. (2023). Artificial Intelligence-Based Supply Chain Resilience for Improving Firm Performance in Emerging Markets. *Journal of Global Operations and Strategic Sourcing*, 17(3), 516–540. <https://doi.org/10.1108/jgoss-06-2022-0049>

- Nurlina, N., Rosa, Y. D., & Yanti, B. (2023). The Effect of Digital Literacy and Business Strategy on the Performance of Micro, Small, and Medium Enterprises (MSMES) in Culinary Industry in Padang City. *International Journal of Progressive Sciences and Technologies*, 38(2), 252. <https://doi.org/10.52155/ijpsat.v38.2.5291>
- Pranata, S. (2024). Content Marketing, Social Media Marketing and Search Engine Optimization (SEO) on Successful Business Performance in Msmes in Cirebon City With Digital Literacy as an Intervening Variabl. *Jurnal Riset Ekonomi Manajemen (Rekomen)*, 7(1), 272–283. <https://doi.org/10.31002/rekomen.v7i1.1426>
- Rogers, E. M., & Everett, M. (1983). *DIFFUSION OF Third Edition*. teddykw2.files.wordpress.com/.../everett-m-rogers-diffusion-of-innovati..
- Santosa, A. D. (2024). Artificial Intelligence (AI) Adoption as Marketing Tools Among Micro, Small, and Medium Enterprises (MSMEs) in Indonesia. *Jurnal Sosial Humaniora*, 17(1), 91. <https://doi.org/10.12962/j24433527.v17i1.20520>
- Seriki, O. (2020). *Resource-Based View*. 1–4. https://doi.org/10.1007/978-3-030-02006-4_469-1
- Tresnasari, R., & Zulganef, Z. (2023). Increasing MSME Performance Through Institutional Strengthening, Entrepreneurship, and Digital Marketing. *International Journal of Research in Community Service*, 4(1), 11–17. <https://doi.org/10.46336/ijrcs.v4i1.383>
- Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Wang, Y., Zhang, X., & Wang, L. (2022). Assessing the Intention to Use Sports Bracelets Among Chinese University Students: An Extension of Technology Acceptance Model With Sports Motivation. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.846594>